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# NEW APPROACHES OF THE FORECAST OF THE AGEING OF PLASMA JET NOZZLE IN INDUSTRIAL SETTINGS OF THERMAL SPRAYING

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## - Summary

The optimization of the extension of the timelife of the torches without hazard of drop of the product is an unceasing industrial difficulty. It needs a reliable criterion to characterize the wear, and thus indicate when the nozzle used should be switched by a new nozzle. These criteria are still quite subjective and hold the operator's experience. In 2003, David RIGOT, in collaboration with the Volvo Aero Corporation, has defined a number of criteria in his thesis dissertation [1]. This study led to the realization of an electronic module alert detecting the hazardous time of process. The focus method was based on research and tracking characteristic frequencies in arc voltage fluctuations and in acoustic noise that is the image. It seems that a rough statistical study of signals is able to help define and visualize simple criteria ruthless variation is usable in objective phenomena wear alert. This is ad hoc measures for smooth power spectrum [2] [3] and its variability. Filtered signal is used to distinguish typically one or two epochs of slow wear followed by an epoch of fast wear. This difference is clear after a suitable choice of used frequency bands. Graphical representations are very expressive; they are supplemented by statistical tests. Signals & method: results, by David RIGOT on campaign made shots in September 2003 at the aircraft manufacturer Volvo Aero. Files led to collect a series of measures standardized on the time life of the nozzles. For one, whose use was particularly long, a few shots "vacuum" were prosecuted beyond of the usual threshold used in order to study the ageing. Sound torch and tension thus collected at various times of operation nozzles, with several frequencies of sampling, feed and no feed of powder. They allow first approach directly extract global statistical parameters which it represents dissimilarity based on time: moments, skewness, kurtosis, entropy [4]. To each power spectra measurement, time is calculated from each signal multiple sampling. Each of the frequencies spectra is smooth inside of a convolution window by a kernel assessor [5]. A simultaneous representation of the power of signals and their erraticism are used to visually choose the most discriminating frequency bands. Two groups of settings are then assessed: mean and variance of spectrum in the band selected; global parameters newly evaluated from filtered in the chosen band signals. Results: most selective statistics evolve in a similar manner and allows periods wear, while the overall results are most often efficient. For example templates to slope failure (piecewise linear models) are used. The spectra of tension frequencies and the spectra of sound frequencies give similar results. The sound is usable with the feed or without feed of powder. Sequential simple tests may be expected to assess the time of rapid wear.

## Aim of this study

However the plasma projection industry faces growing performance requirements and more stringent requirements. The answer to these constraints requires a better understanding of the phenomena involved in the process of plasma projection (fluctuations in the foot of arc phenomenon of particle dispersion of powder, interaction plasma-particle, impact of particles on substrate,...), and better tools for diagnosis and prediction (control online and model digital). It is the task that it is proposed the SPCTS laboratory and for which he seeks the cooperation of the scientific community. More than thirty years on the methods of treatment of materials by plasma and its experimental work and simulations have covered the areas of process with successively reactor plasmas [6], [7], [8], [9], the study of chemical thermodynamics and transport in plasma properties and the database T&TWinner [10], [11], [12], [13], [14], [15], [16], [17] electric arc [18], [19] plasma jet training, design and flare plasma metrology [20], [21], [22], [23], [24], the treatment of particles flying [25], [26] and their impact on the substrate [27], [28], [29], [30], [31]. This production was possible because the laboratory still is equipped with means of diagnosis and control online and it has developed digital variable complexity tools he needed.

Thermal projection industry is subject to high stresses of reproducibility and reliability of deposits since the parts to have a high added value. The controls in the deposit lines naturally took an important place during recent years. In effect the erosion of electrode in plasma flare a decrease of the enthalpy of the plasma flame and consequently decreased speed and the temperature of the projected particles. This modifies the final properties of the deposit in the best of cases, and leads to its destruction by incorporation of metal particles of the electrodes in the case of the latter too much wear. Various online techniques that exist currently consist mainly to follow the change of temperature and speed of the particles in flight or hot particle flux distributions. It is an indirect method to estimate the effectiveness of a torch and correct the effects of the erosion of the electrodes on the heating and acceleration of the particles. But there is not this update method to directly diagnose the erosion of the electrodes. Numerous studies have already shown that the voltage at the terminals of the electrodes changes their State of wear, but no theory has yet developed to help understand the phenomena of erosion and no apparatus for direct control of the State of the electrodes is available at the present time. Very soon the scientific community has studied these problems of electrode wear [32,33], without however. This is to compensate for this deficiency that Volvo Aero Corporation and the SPCTS laboratory joint their efforts to support the work of David Rigot [1] on the following objectives: determine indicators parameters of the State of a torch at a time given its use, follow the evolution of these different indicators and select those that are most relevant to control the erosion of electrode wear. The erosion of the nozzle is attributed to the permanent displacement of the foot of arc on the surface of the electrode as a result of magneto hydrodynamic forces. These fluctuations in the foot of arc translate by fluctuations of the voltage at the terminals of the electrodes and strongly contribute to the emission of the sound by the torch [34, 35, 36, 37]. These two measurable phenomena are studied. The difficulty lies in the difference of time scales between the fluctuations of the foot of arc (in the area of the 100 to 500 $\mu$ s) and the development of erosion (in the tens of hours). Here a new statistical analysis is presented which tends to resolve this problem.

## - Materials and Methods

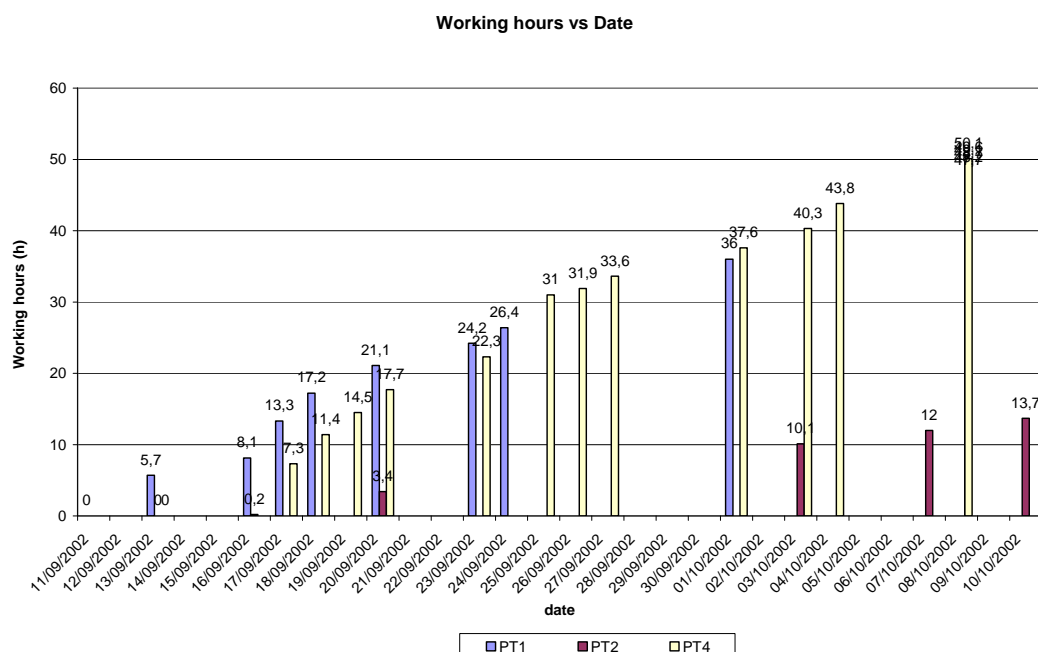
### Record of experimental data

The experiment was carried out between September and October 2002 by D. Rigot [1,38, 39, 40] within the Volvo Aero Corporation SE – 461 81 Trollhättan, Sweden, in real industrial conditions. On the four plasma spray torches that were in use at this time (**Figure 1** and Figure 2), two of them reach their end of life and give sufficient data. Plasma torch 1 had a regular lifetime of 36 hours while torch 4 had an outstanding long lifetime of 47.7 hours.

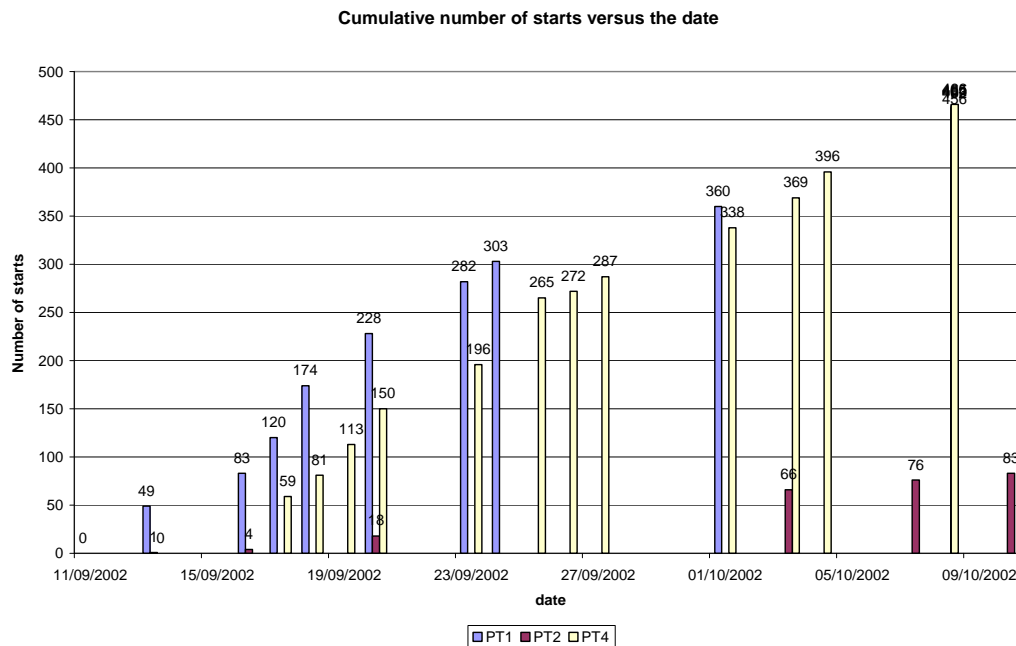
The starts were quite regular in this experiment, so that we are unable to differentiate absolute time from relative time such as the number of starts. The data collected at each shooting were the sound emitted by the torch and the torch voltage between electrodes. The data analysis was carried out using Matlab® R12 (41) and Systat® 10.2 (42).

Sound was sampled at 8000Hz and recorded in a standardised manner (Figure 3 ): one record with powder feed, the other one without powder feed. Recordings last each one a few to about ten minutes. There were saved first by D. Rigot [1] in the wave file “\*.wav” format.

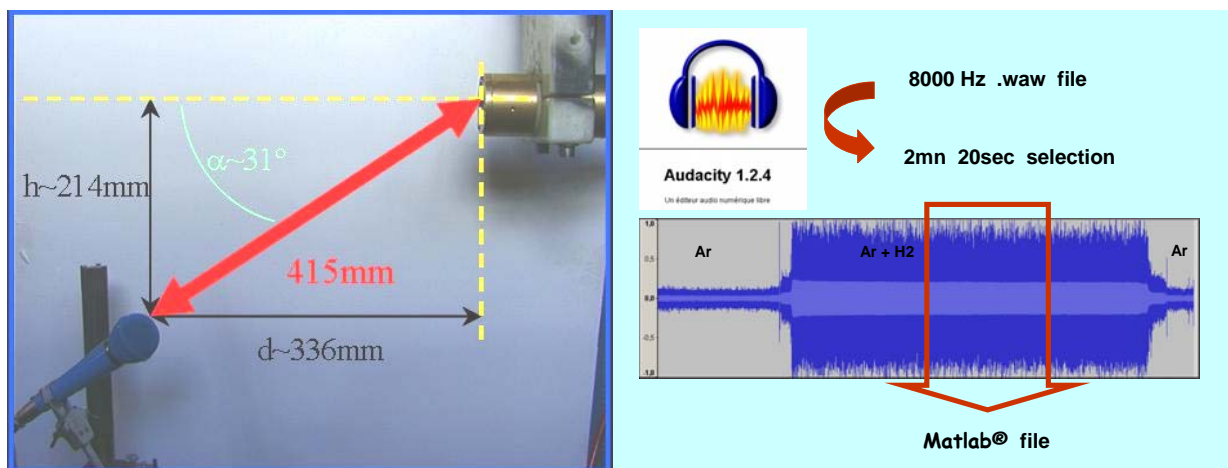
For the purpose of this study, we extract from the middle of each recording a subset of 2 minutes 20 seconds holding more than  $2^{20}$  data and transformed it to the Matlab format with the free software Audacity 1.2.4. Voltage data were sampled with a digital signal processor and Labview® 6.1 at 5000Hz for one second and at 50000Hz for 0.1 second. The Matlab load function is used to exploit the recorded text files. In this paper all the data are analysed after rescaling of amplitudes of the signal samples between -1 and +1 limits.



**Figure 1 – Working time in hours versus date for the four plasma torches**



**Figure 2 – Cumulative number of starts versus date for the four plasma torches**



**Figure 3 - Scheme of the sound measurement and signal sample.**

## Experimental data analysis

Some potential criterions of anode erosion are computed from whole and filtered data of each shooting. Filtering is definite on the basis of the graphic representation of both trend and variance of power spectra. Smoothing greatly reduces the huge variability of spectra so that one can observe larger variations and sampling variance (**Figure 4**). So the more convenient frequency bands are easily defined. In short we get statistics from the original and filtered signals and from the corresponding whole and partial smoothed spectra (**Figure 5**).

Each curve corresponds to one independent subset of data. Each subset is centred and its power spectrum is obtained by Fast Fourier Transform (FFT). Filtering is carried out by inverse FFT

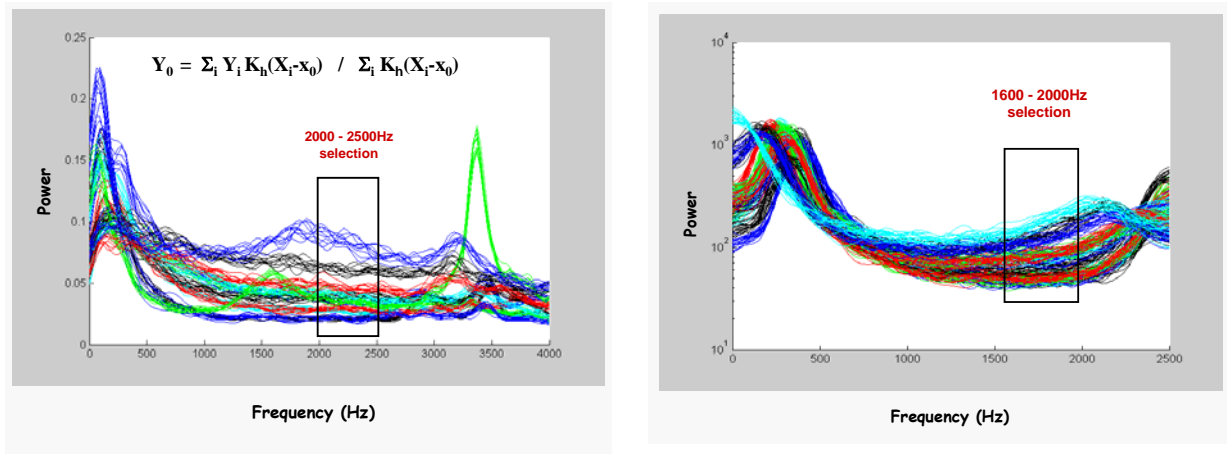
of the selected frequency band. Smoothing is performed by the Nadaraya-Watson (NW) kernel estimator. Consider the power  $p_j$  at frequency  $f_j$ . The NW estimate of  $p_j$  is given by:

$$NW(p_j) = \sum_i P_i K_h(f_i - f_j) / \sum_i K_h(f_i - f_j)$$

where  $K$  is the weighting function and  $h$  a parameter that control the width of the smoothing window. Here  $K$  is the Gaussian kernel

$$K_h(x) = h^{-1} (2\pi)^{-1/2} \exp(-x^2/h^2)$$

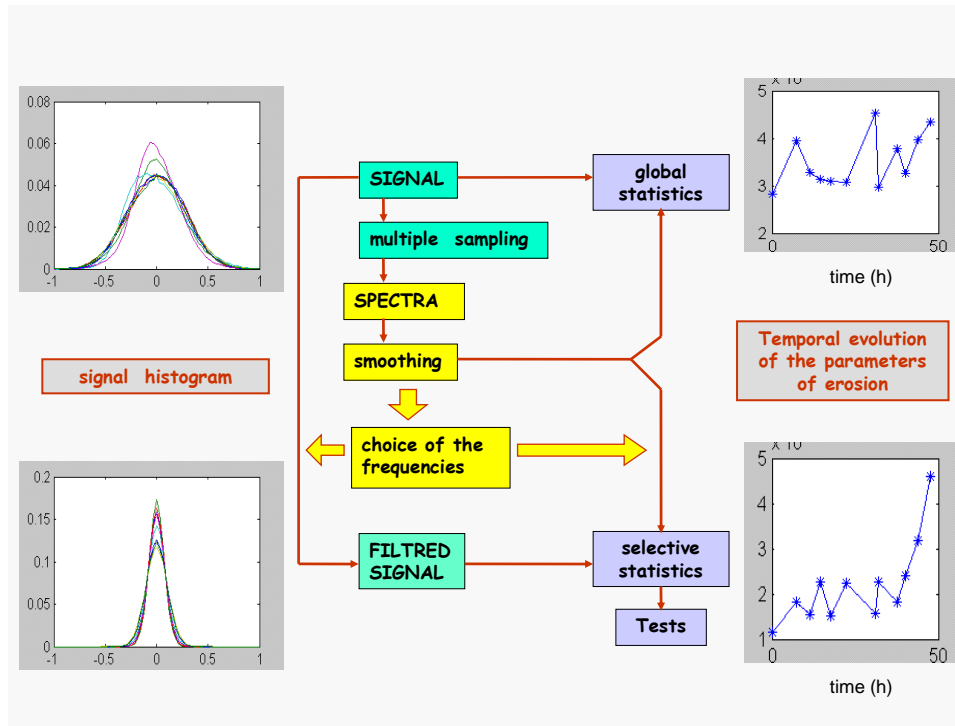
which was chosen for its smoothness. This calculus is quite slow but it may be preferred to fast convolution algorithms to avoid the effect of rounding errors [43]. The simple NW estimator may be replaced by other local estimators [3]. There are also many alternatives to the Gaussian kernel [2]. For sounds, we used 64 independent samples of  $2^{14}$  data (~2 sec.). The window smoothing parameter  $h$  was about 40-60 Hz for visualisation but half for calculus. For visualisation purpose, the number of estimates must be important enough for a smoothed representation. For statistics we want to neglect the covariances induced by smoothing, so we need a distance more than  $4 \cdot h$  between point estimates with the Gaussian kernel. With  $h=20$  Hz we can estimate up to 50 points between 0 and 4000 Hz and no more than 6 points for a 500 Hz band for example. In the case of tension, the available data were lower with only  $2^{12}$  data (~0.82 sec.) for each of 30 samples. We used a parameter  $h=30$  Hz for smoothing, and so we estimate 41 points for the whole sample and 3 points for a 400 Hz band.



**Figure 4 - Sampling and smoothing of plasma torch 4 signals: [a] Sound, [b] Tension. Colors correspond to working times. Note that logging gives similar variability of spectra across time.**

The statistics taken into account are entropy and centred moments. The entropy is evaluated from 63 intervals between the -1 and +1 limits:  $ENT = - \sum_k p_k \log(p_k)$  where  $p_k$  is the proportion of data falling in interval  $k$ . The centred moment of order  $k$  of  $n$  data  $\{x_i\}$  is defined as  $M_k = n^{-1} |\sum_i (x_i - m)^k|^{1/k}$ . Variance, skewness and kurtosis can be deduced for  $k=2, 3, 4$  but we prefer centred moments because they are on the same scale.

Multiple sampling and smoothing of the spectra allow evaluating the local mean and variance (VAR) for any frequency. For a frequency band, we got an estimate of the mean (the mean of means) and of the conditional variance (CVAR, the mean of the local VAR). Smoothing causes covariances between power estimates. In practice a distance between frequencies more than  $4h$  allow to neglect these covariances with the Gaussian kernel.



**Figure 5 - Data analysis outline. Statistics are computed from non-filtered and filtered signals, and from their respective smoothed power spectra.**

## Erosion modelling, testing and forecasting

To our knowledge, there does not exist to date any established model of anode erosion based on a temporal evolution of objective criterions of wear. The choice of a model will thus be done in a pragmatic way and as simple as possible. The goal is to detect if it exists some threshold in the evolution of the measured statistics. The considerable experimental work of D. Rigot [1] allowed us to better target the interesting criterions. Multiple sampling gives the advantage of estimating simultaneously means and variances. This is the basis of statistical modelling and estimation (**Figure 5**).

A very simple threshold model is the piecewise linear regression model. If we detect two periods in the torch life, we can express a measure  $y$  in function of time  $t$  as

$$y(t)-y_0 = [a(t-t_0)]*(t \leq t_0) + [b(t-t_0)]*(t > t_0) ,$$

where  $\{t_0, y_0\}$  are the coordinates of the threshold,  $a$  and  $b$  the trends of  $y$  in the two successive periods. Estimation of the four parameters is made by non-linear regression methods. With the aid of multiple sampling, we are able to elaborate a model for the variance of the measures. This will determine the need of a transformation or a weighting of  $y(t)$ . Weighting is necessary when the variance vary with  $t$  or  $y(t)$ . A transformation is preferred when it simultaneously normalises the error distribution and homogenates the variances so that weighting become unnecessary. It is based on the mean-variance relationship.

When a large deviation is visually detected, we will test it with the prediction limits provided by the linear regression of the mean powers vs. time. For each value of time, the prediction error depends on three terms: a standard deviation  $SD$ , the error of the regression  $(1/n*SD)$ , and the distance of the predicted value. Because we are only interested by positive deviates, we will use

unilateral tests. When the error is estimated by the residual error, the upper prediction curve UPC for a given risk is computed on the basis of the Student cumulative function TCF with N-2 degrees of freedom for N measures. For a 95% confidence level (risk=5%) and for a given working time  $t_j$ ,

$$UPC(t_j) = [a+b*t_j] + TCF(0.95, N-2) * SDP(t_j) .$$

SDP( $t_j$ ) is the standard deviation of the prediction at time  $t_j$ :

$$SDP(t_j) = SD * [ 1 + 1/n + (t_j - \bar{t})^2 / \sum((t_i - \bar{t})^2) ]^{1/2} ,$$

where  $t_i$  are the observed time values,  $\bar{t}$  the mean of the  $t_i$ . We will discuss on the choice of the measured error or the estimated residual error for SD. In the case of a known error, the TCF function is replaced by the normal cumulative function NCF.

As piecewise and simple linear models are nested, we may confirm the piecewise model with a likelihood ratio test. When using ordinary least squares, this test reduce to a simple Fisher test between two variances: the mean square of the difference of fitting of the two models and the mean square of the residual error estimate of the more general model, i.e. the piecewise model. Consider  $H_0$  as the one piece linear regression model and  $H_1$  the two pieces linear regression model estimated with N measures, RSS0 and RSS1 their respective residual sum of squares,  $p_0$  and  $p_1$  their respective number of parameters. We will calculate the Fischer cumulative function

$$FCF ( [(RSS0-RSS1)/(p_1-p_0)] / [RSS1/(N-p_1)] ) ,$$

with  $(p_1-p_0)$  and  $(N-p_1)$  degrees of freedom, and possibly reject  $H_0$  with an error risk  $= (1-FCF)$ .

Another problem is the prediction of the lifetime of the torches. It is approached here in the simplest manner, were this lifetime is a linear function of the estimated parameters and a power threshold set by the user. We use the function FUNPAR of Systat<sup>®</sup> nonlinear estimation procedure to calculate confidence intervals for the predicted lifetime. More advanced methods exist for this inverse problem but they are not presented here.

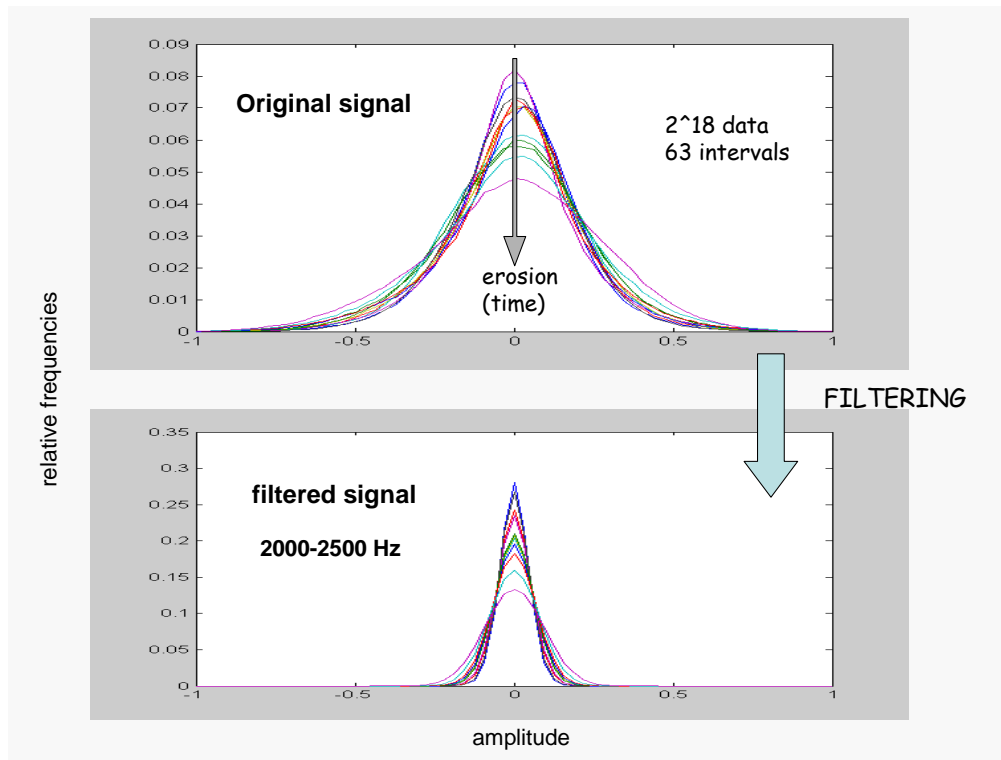
## **- Results**

### **The effects of filtering**

The useful frequencies are determined visually from the smoothed power spectra. The tension sampled at 50000 Hz gives no results of interest. We easily see stable and homogenate bands between 1500 and 3000Hz for the sound signals and between 1300 and 2200 Hz for the tension signals. We choose the corresponding filtering by keeping the 2000-2500 Hz and 1600-2000 Hz bands, respectively. We are now able to compare the statistics evaluated from unfiltered and filtered signals, and their time dependence (**Figure 6**):

- from the signals themselves
- from their power spectra, whose conditional variances give a confidence interval for each value.

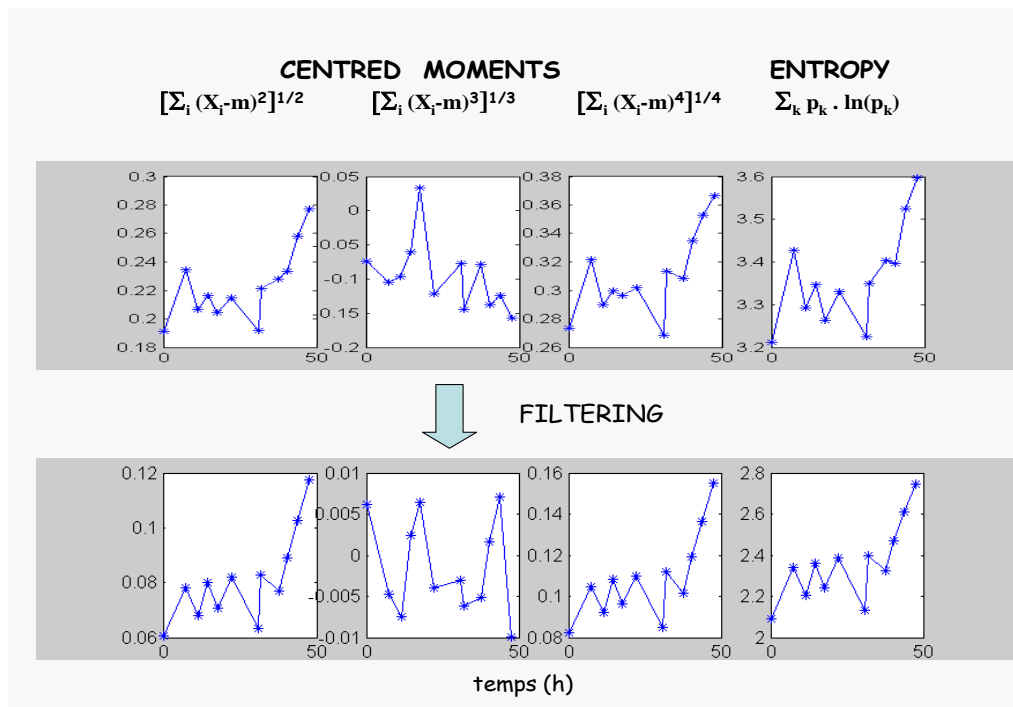




**Figure 6 - Evolution of the amplitude histograms, computed starting from the original and filtered signals (plasma torch 4, no powder feed)**

### 1- Signals:

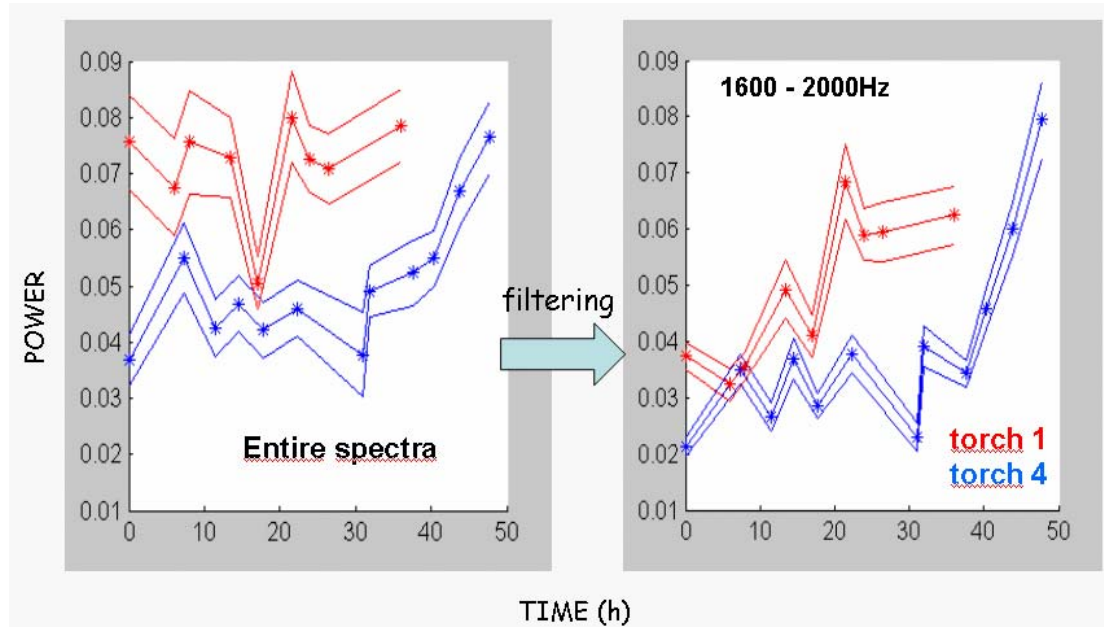
Filtering improves the relations between erosion and time very clearly (**Figure 7**). Even moments and entropy evolve in a very similar way in function of time. The shape of the trend allows us to hypothesize two periods of wear: a period of relatively slow erosion followed by a more rapid one. That seems to confirm the existence of a threshold in the phenomena of wear of the torches.



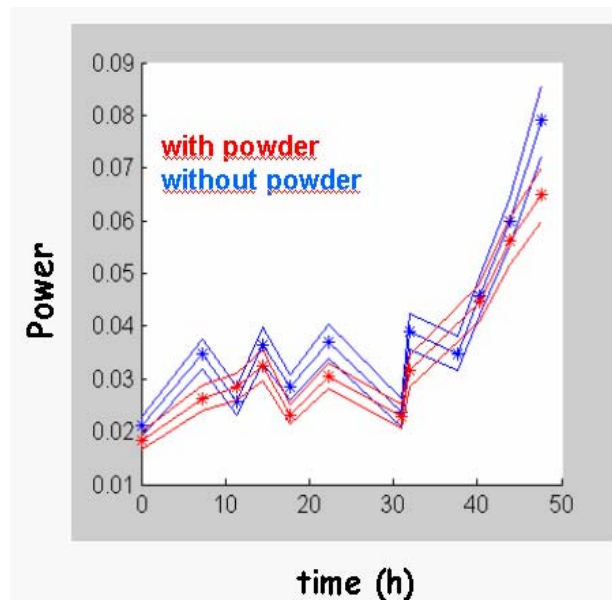
**Figure 7 - Evolution of some potential criteria of erosion, computed starting from the original and filtered signals (torch 4, no powder feed)**

## 2- Power spectra

The trends obtained from power spectra are similar to those of moments or entropy, but power spectra give improved results: a standard deviation of powers around each mean. So a standardised measure of sound can be related to the anode erosion. The second result is that the sound can be sampled either with or without the presence of powder: the powder injections do not disturb much the sound recordings which remain exploitable in spite of a bigger variability (Figure 8).



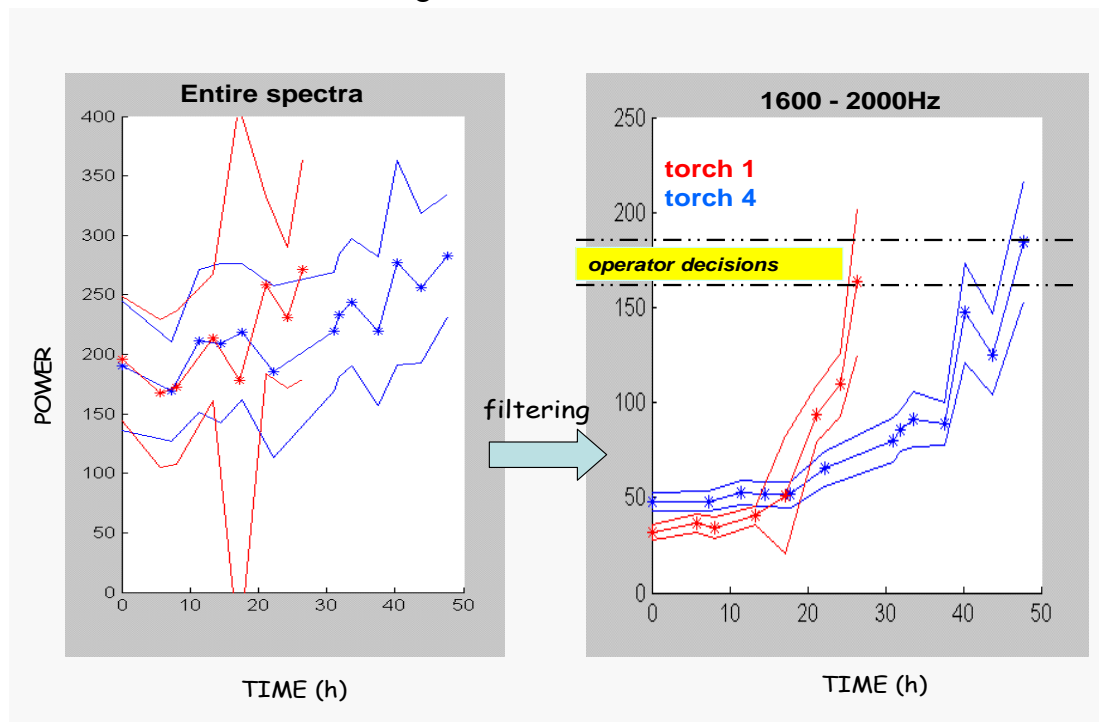
**Figure 8 - The effect of filtering on sound spectra. Means and confidence intervals of smoothed powers in function of working time (torch 1 and 4, no powder).**



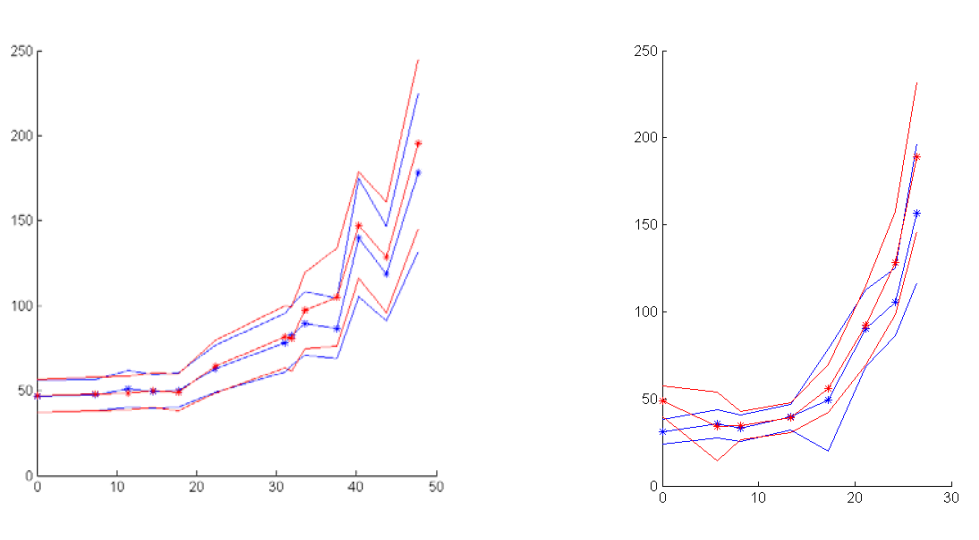
**Figure 9 - Effect of powder feed on the filtered sound spectra (plasma torch 4).**

Filtering is particularly spectacular in the case of tension spectra. After filtering, the tension appears of weaker variance than the corresponding samples of sound. The hypothesised

threshold is still more visible. The power seems a little bigger in the presence of powder (**Figure 9**), but the difference is small. One of the two first measures for the torch 1 is clearly abnormal and will be discarded in the following.



**Figure 10 - The effect of filtering on tension spectra. Means and confidence intervals of smoothed powers in function of working time (plasma torch 1 and plasma torch 4, without powder feed).**



**Figure 11 - Repeatability between the two series of measures of tension (with and without powder). Left: torch 4, right: torch 1. The lines connect means and confidence intervals of the smoothed powers.**

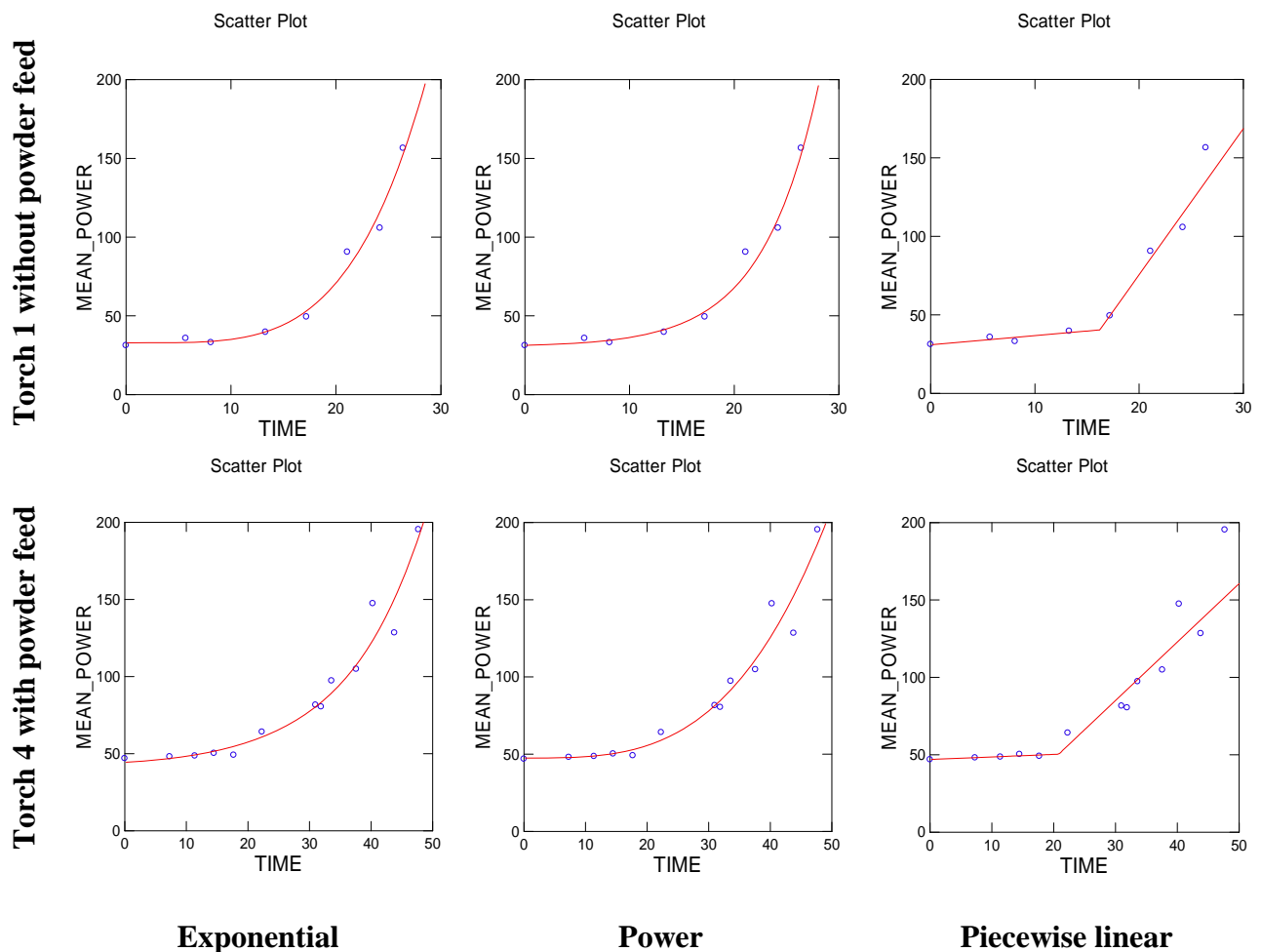
We note that the two torches were stopped near the same power value (**Figure 10** and **Figure 11**). The experience of the operator is of great importance. The stopping power value is also

about four times the starting one. Two experiments are not sufficient to say if the operator experience can be related to a fixed power or to a relative one.

## Statistical modeling

### 1- Competing models

We want to determinate a threshold as an alert in the erosion process. Even if the true relation seems exponential or power, it can be approximated by linear pieces. We see than a two-piece linear model fits also very well when restricted to the lifetime of the torches and better corresponds to our goal (**Figure 12**). The long lifetime of torch 4 is explained by a difference of 4 hours between the thresholds but especially by a slower increase of power in the second period. The choice between the three models comes from variance study.



**Figure 12 – Modeling of tension power spectra: comparison of exponential, power and piecewise linear models. Top: plasma torch 4 with powder feed. Bottom: Torch 1 without power feed.**

### 2- Variance modelling

From the usual assumptions that apply to regression and analysis of variance we note: normally distributed error terms, homogeneous variances of different samples, means and variances not

correlated. None of these points is checked with the current data. There exist advanced methods that can circumvent some of these problems (iteratively reweighed least squares, general least squares...) but often an adequate variance-stabilizing transformation of the data can solve them all. This transformation is driven from the link between means and variances in log-log scales.

From the kernel estimates of the power spectra, we see that standard deviations (SD) are strongly related to means. They can be modelled by  $SD = 0.12 * \text{Mean}$  (not represented), while the slope in log-log scales is close to 1 (Figure 13left). This slope suggests logging values to get similar variances along the erosion process. Note that it is not a simple logging of the mean powers: spectra are logged then smoothed so that we get means of logged powers.

We verify that logging the power values homogenises the variances: we get from the overall a variance of the logged power values close to 0.0036, i.e. a reference SD of 0.6 (Figure 13 right).

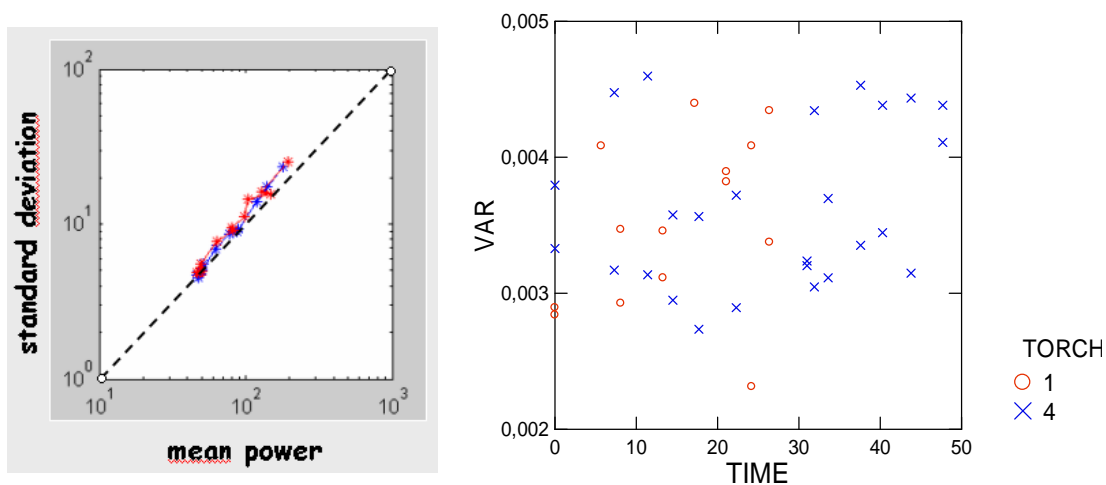
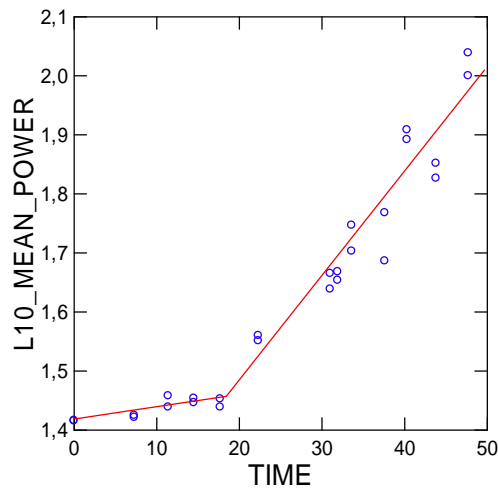


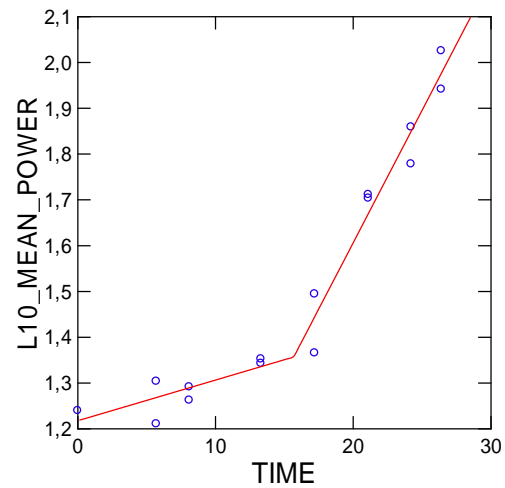
Figure 13 – Left: relationship between standard deviations and means of the tension spectra (log-log scale). Right: variance of logged data across time

### 3- Statistical alert: an example

Logging the power values gives a great simplification of the variance model: the variance is constant so we don't need weighting any more. Exponential or power models can't be fitted anymore. The first statement is that the two estimated thresholds are closer with logged values than with natural values (Figure 14). The second is that the standard deviations (SD) of the residual errors (0.043 and 0.049) are lower than the measured reference SD (0.06). We must be careful with regression witch gives only an adjustment error depending on the number of points. We will use in the following the measured value 0.06 witch is independent of the number of samples. It is important in the following iterative procedure involved. This is another advantage of multiple sampling.



**Plasma Torch 4, all values**



**Plasma Torch 1, all values**

**Figure 14 – Piecewise linear model with logged data.**

Consider now that we are in a real situation: we have reached 14 hours of working without any trouble and we want some kind of confidence interval for the next values. Because we are interested only by increasing values, we will only consider an upper confidence curve UPC. The upper prediction curve (UPC) is computed from the regression function and the predictive standard deviation SDP. Because we use a known error instead of an estimated one the Normal cumulative function (NCF) is involve instead of the Student's one:

$$UPC(tj) = [a+b*tj] + NCF(risk) * SDP(tj)$$

We detail the procedure for plasma torch 1 (cf. formulas in \$ erosion modelling). The ordinary linear regression for Time<15 hours gives:

$$mean\_l10power = 1.22 + 0.0089*time$$

SDP for a given time tj is:

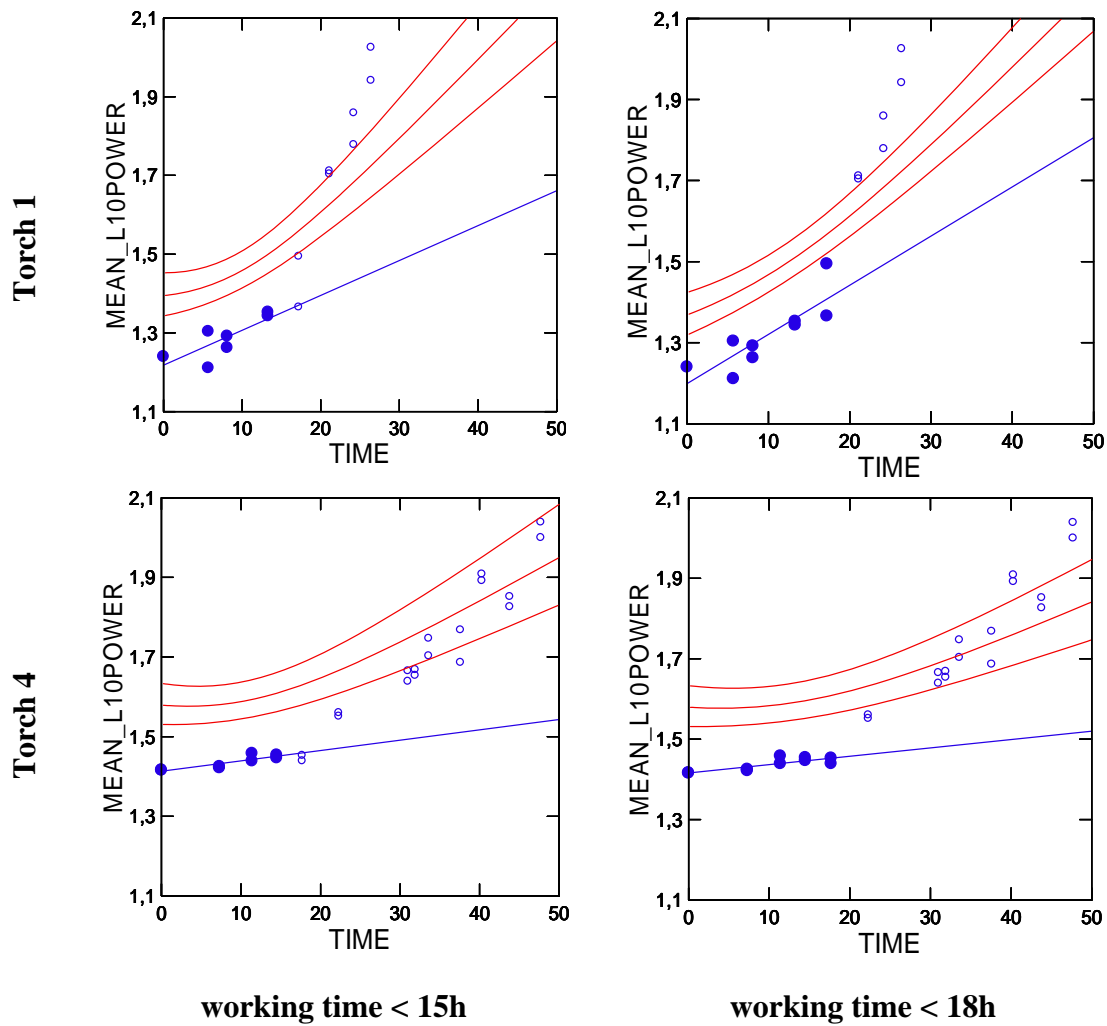
$$SDP(tj) = 0.06 * [8/7 + (tj-7.74)^2 / 130]^{1/2}$$

We note that the following points (time=17.2 hours) are below the 95% confidence curve (**Figure 15 up left**). We can't reject that these points belong to the first period. We can include now these points and repeat the procedure for Time<18h. At 21.1h the two points are above the upper confidence curve (**Figure 15 up right**). Linearity can be rejected with an error risk < 0.1%. We have detected a great variation in the erosion process.

Consider now torch 4 (**Figure 15 down**): because the slope of anode erosion is weaker than for torch 1, there is more difficulty to detect a large departure from the linear trend of the first period. We can reject the linearity only after 31 hours of working with a risk < 5% or after 40h with a lower risk of 0.1%.

#### 4- Confirmation of the piecewise model: another alert procedure

Consider that we observed the next measures and that the rupture of slope seems to be confirmed visually. Because the simple regression (H0 hypothesis) is a special case of the more general piecewise linear model (H1 hypothesis), they can be compared by likelihood ratio test. Using least squares, this test reduces to F test between two variances. The first one is the difference of fitting of the two models while the second is the residual error of the more general model H1 (cf formulas in \$ erosion modelling).

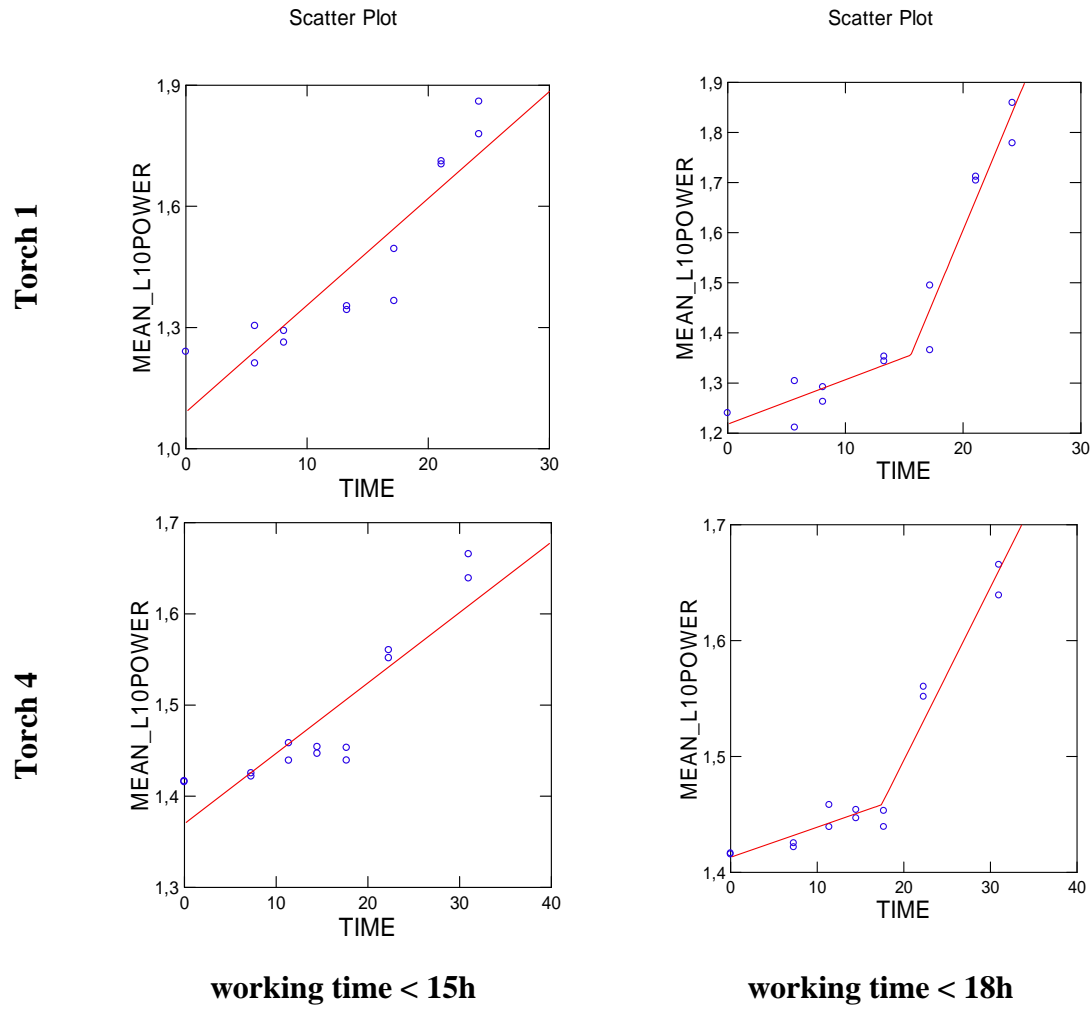


**Figure 15- Prediction confidence curves for risks 5%, 1% and 0.1% (tension data).**

For torch 1 and time<25h,  $p_0=2$ ,  $p_1=4$ ,  $N=13$ . We have also:  $\text{Var}(H1 - H0) = (0.10771 - 0.02265)/2 = 0.04753$  and  $\text{Var}(H1) = 0.02265/9 = 0.00252$ . We now calculate the Fischer cumulative function  $\text{FCF}(0.04753/0.00252)$  with 2 and 9 degrees of freedom.  $\text{FCF}=0.9994$  so that the simple model can be rejected with a risk  $< 0.01\%$ . For torch 4 and time <31.5 we get a result even better.

Testing models seems more efficient than prediction. In fact the two tests are not based on the same error: the first is based on the variance measured by multiple sampling, the second on the residual variance estimated by the regression model. Because the measured variance is larger than the estimated one, the first test is conservative and is adequate to detect safely large divergences from the simple linear model.

The tests widely depend on the quality of regression of the first measures, and on the number of these measures. The residual error is much lower for plasma torch 4, may be by good luck! This is not a good way to proceed if we want to elaborate a standardised monitoring.



**Figure 16 – Piecewise model confirmation tests (tension data)**

From the two torch examples (**Figure 16**), it seems essential to proceed to regular measures in the first 16 hours and stay with these values for the following tests. Then the new measures are tested with the confidence limits estimated from the first 16 hours and the fixed measured error from the power spectra. In the current study there are not enough measures in the first period and the second period is worse! It seems reasonable to make at least a measurement per hour during the first 16 hours and twice more after this period of security, when the speed of erosion is capable of a quick increasing.

## 5- Prediction of the lifetime

We need a limit value  $t_{lim}$  for a limit power  $y_{lim}$  to be reached. For example, we will hypothesise that the two torches have been stopped because the mean power have exceed the value  $y_{lim}=1.9$  in  $\log_{10}$  scale (this hypothesis has to be confirmed by other experiments). In this case, the lifetime is shorter when the slopes of the model are greater. The estimation take place in the second period with slope  $b$ , so that we have for the point  $\{y_{lim}, t_{lim}\}$ :  $t_{lim}=t_0+(y_{lim}-y_0)/b$ , and a confidence interval can be computed for  $t_{lim}$ .



For torch 1, there are not enough points in the second period: we reach  $y_{lim}$  at the same time we are able to confirm the piecewise model. Table 1 presents detailed results for torch 4. They compare estimations based on working time  $< 31.5$  with full working time.

	time life < 31.5			whole points		
Parameter	Estimate	Wald 95% Conf. Interval		Estimate	Wald 95% Conf. Interval	
		Lower	Upper		Lower	Upper
<b>A</b>	0,00260	0,00015	0,00504	0,00208	-0,00247	0,00663
<b>T0</b>	17,42750	14,60186	20,25314	18,76572	14,07377	23,45767
<b>Y0</b>	1,45833	1,42649	1,49017	1,45482	1,39986	1,50978
<b>B</b>	0,01492	0,01214	0,01770	0,01769	0,01475	0,02062
<b>TLIM</b>	47,03626	42,55865	51,51387	43,93431	42,12269	45,74593

**Table 1 – Parameter Estimates for plasma torch 4.**

The estimated  $t_{lim}=47$  is quite good compared with the whole points estimate 44. We can take its lower confidence value = 42.5 as a limit for a reasonable lifetime. Above 42 hours, the process may be continued with great care, depending on the experience of the operator. This estimation can be repeated each time new values are introduced in the model.

The prediction of the lifetime corresponds to an inverse estimation problem, as for calibration curves. The symmetric Wald confidence interval is not the best one, and more accurate estimates and asymmetrical intervals can be involved with Cook-Weisberg intervals, Monte-Carlo or Bayesian methods. We just want to show here that it is possible.

## **- Conclusion**

The filtering of the signals makes it possible to define two stages of alarm during the working process. The first is given by a threshold model which detect an important variation of speed in the erosion process. The second is based on an estimation of the lifetime of the torch. These two values separate three periods: a safe period with low speed erosion, a critical period where the erosion progress quickly, and a hazardous period which require a great attention from the operators. All the values estimated or advised must be improved by new experiments in industrial condition of working.

**Life Memorial :** in memory of David RIGOT died on October 3<sup>rd</sup> 2007  
Guy DELLUC died on December 15<sup>th</sup> 2003  
Guy TREILLARD died on August 29<sup>th</sup> 1997

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## Nomenclature

$H_0$	Null hypothesis
$H_1$	Alternate hypothesis
FCF	Fisher cumulative function
FFT	Fast Fourier Transform
$h$	Frequency [Hertz]
NCF	
NW	Nadaraya-Watson estimator
SD	Standard deviation
SDP	Standard deviation of prediction
SCF	Student cumulative function
Var(x)	Variance of variable x
UCL	Upper confidence limit

## Subscripts

$i$	index
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